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THE EFFECT OF POSTSECONDARY EDUCATIONAL INSTITUTIONS ON LOCAL ECONOMIES: A BIRD'S-EYE VIEW

Patrick Lehnert
Madison Dell
Uschi Backes-Gellner
Eric Bettinger

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ABSTRACT

Despite worldwide expansion of higher education, the impact of higher education institutions on local economic activity is still poorly understood. We analyze the local economic effects of branch campus openings in Tennessee and Texas, two states representative of the underlying U.S. enrollment patterns. To overcome the lack of adequate data, we use a novel proxy for regional economic activity based on daytime satellite imagery. Applying different panel methods—traditional difference-in-differences (DD), heterogeneity-robust DD, and instrumental variables—we find positive effects. Independent data show an increase in college graduates and employment in the sectors aligned with programs offered at branch campuses.

Patrick Lehnert
Universität Zürich
patrick.lehnert@business.uzh.ch

Uschi Backes-Gellner
Universität Zürich
backes-gellner@business.uzh.ch

Madison Dell
Stanford School of Education
mdell908@stanford.edu

Eric Bettinger
Stanford School of Education
CERAS 522, 520 Galvez Mall
Stanford, CA 94305
and NBER
ebettinger@stanford.edu

1. Introduction

For over half a century, nations have heavily expanded higher education institutions as catalysts for regional or local economic growth and individual returns. Similarly, the strategic expansion of higher education campuses in the U.S. since the 1980s had two main goals: (a) fostering regional economic development for generating social returns and (b) meeting the increased demand for higher education by individuals who expect private returns. Numerous economic studies from a variety of countries examine individual private returns to higher education and find positive effects.[1]

However, evidence on fostering regional, and particularly local, economic growth remains elusive. Previous literature that studies the effects of higher education expansions at disaggregated levels focuses mainly on college attainment, employment, firm development, or innovation and patenting.[2] The scarcity of evidence on local economic growth[3] results mainly from the lack of appropriate data at sufficiently disaggregated regional levels and for the required time periods. Measuring the local economic impact of educational institutions is difficult as it requires both variation in the availability or opening of educational institutions and reliable economic data that can accurately capture the catchment area of a particular institution both before and after its opening. This is especially difficult in the U.S., where most four-year colleges have existed well before

[1] See, for example, Bianchi and Giorcelli, 2020, and Oppedisano, 2014 for Italy; Böckermann and Haapanen, 2013 for Finland; Currie and Moretti, 2003, Engbom and Moser, 2017, Fortin, 2006, Moretti, 2004a, Mountjoy, 2022, and Oreopoulos and Petronijevic, 2013 for the U.S.; Devereux and Fan, 2011, and Walker and Zhu, 2018 for the United Kingdom; Jung et al., 2016 for South Korea; Kamhöfer et al., 2019 for Germany; and Katzkowicz et al., 2023 for Uruguay.

[2] See, for example, Russell et al., 2022 on college attainment; Gagliardi et al., 2023 on employment; Che and Zhang, 2018, Leten et al., 2014, Moretti, 2004b, Rammer et al., 2020, and Schlegel et al., 2022 on firm development; and Andrews, 2023, Cowan and Zinovyeva, 2013, Fritsch and Slavtchev, 2007, Jaffe, 1989, Li et al., 2023, Pfister et al., 2021, and Toivanen and Väänänen, 2016 on innovation and patenting. Moreover, with some exceptions (Andrews, 2023; Jaffe, 1989; Moretti, 2004b; Russell et al., 2022), these findings on higher education expansions come from contexts outside the U.S. and are thus hardly generalizable to U.S. college branch campuses. The reason is that these campuses focuses on teaching rather than on innovation, research, and scientific discovery.

[3] While few studies analyze the effect of higher education institutions on economic growth, these studies either focus only on specific types of colleges or investigate only rather high levels of aggregation. For example, Kantor and Whalley (2014) study only research universities in U.S. urban regions; Kantor and Whalley (2019) and Liu (2015) focus only on U.S. land-grant colleges from a historical perspective; and Valero and Van Reenen (2019) study economic growth only at highly aggregated subnational levels (across 78 countries). In addition, Ramey (2011, 2021) discusses regional economic impacts of U.S. overall government spending in general, but not of college openings in particular.

systematic data on local economic conditions were accessible.

Our paper provides novel evidence on the local economic impact of the large post-secondary education expansion that took place in the U.S. since the 1980s. For this purpose, we construct a new proxy for economic activity from daytime satellite imagery that is applicable in various contexts beyond studying education expansions. Our analyses focus on the states of Tennessee and Texas for three reasons. First and foremost, these states are exemplary of different types of postsecondary education growth that took place in that time period more generally across the U.S. As the solid lines in Figure 1 show, from 1984 through 2020 (the observation period of our empirical analyses), enrollment at public postsecondary institutions increased by 42.3 percent in Tennessee and by 110.5 percent in Texas.[4] The surge in enrollment occurred across the states and overwhelmed the respective higher education systems. Second, these two states represent two ends of a spectrum of densely populated states with short travel times and high community connectivity on the one hand (i.e., Tennessee) and sparsely populated states with long travel times and low community connectivity on the other (i.e., Texas). Thus, these states provide a comprehensive view of the varying impacts of new educational institutions in diverse demographic and geographic contexts across U.S. states. Third, for these two states, we were able to gather historical data on new college branch campuses, data that are unfortunately not readily available in administrative databases.[5]

To accommodate the enrollment surge, Texas and Tennessee, like many other states, created only very few additional main campuses (dashed lines in figure 1) but, rather, expanded capacity at existing institutions and established branch campuses at new locations. Branch campuses are geographically separate from the main campus and offer two- or four-year programs that students can complete fully at the branch campus location.[6] Between 1984 and 2020, the number of public branch campuses (dotted lines in

[4]According to enrollment data from the National Center for Education Statistics' Digest of Education Statistics.

[5]Even though we can identify the opening of a branch campus, most parent campuses do not distinguish between branch and main campuses when reporting data at state and national levels.

[6]We exclude "special purpose" branch campus locations such as high schools (which offer a limited selection of dual enrollment courses that may or may not lead to a degree) and prisons (which offer a limited selection of courses and/or programs to currently incarcerated individuals). In Tennessee, what we refer to as branch campuses in this paper are called "off-campus centers" when they are affiliated with a community

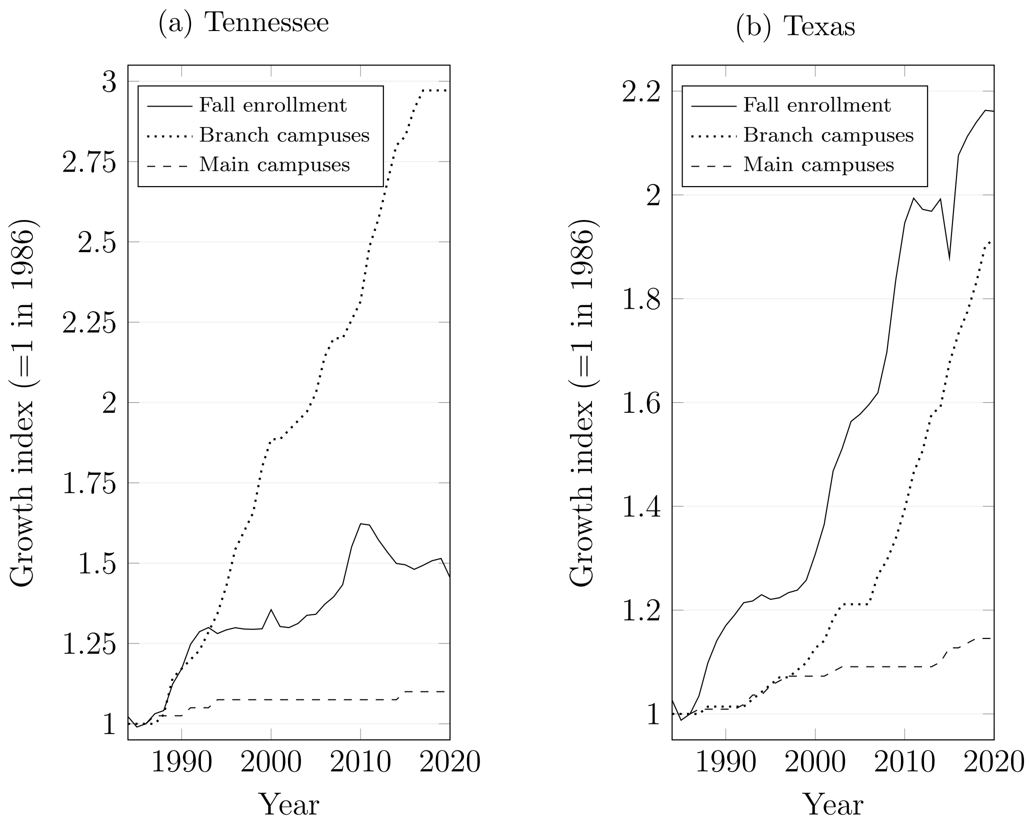


Figure 1: Growth in Fall Enrollment and Number of College Campuses in Tennessee and Texas, 1984–2020

Notes: The figure plots the growth in fall enrollment and number of public college campuses in Tennessee and Texas from 1984 through 2020. We retrieve fall enrollment from the Digest of Education Statistics. We infer the number of branch campuses from our own data collection of branch campus opening years (see Section 3) and the number of main campuses from an institution's first reporting in year in the Integrated Postsecondary Education Data System (IPEDS). The growth index equals 1 in 1986, because it is the first reporting year for most institutions in IPEDS.

figure 1) increased substantially from 35 to 104 (197.1%) in Tennessee and from 71 to 136 (91.5%) in Texas.

This expansion of postsecondary education institutions via branch campuses is the focus of our research. Specifically, we measure the causal impact of the establishment of branch campuses on economic growth in the local communities and surrounding regions.

Identifying causal effects of branch campuses is difficult because their location may be endogenous to the local economic conditions. For example, states may see a branch campus as a strategy to revitalize a struggling local economy. Creating a more educated supply of local labor may attract industry to communities experiencing economic declines. Alternatively, states and institutions may choose to open branch campuses in communities already experiencing economic growth and therefore have urgent workforce demands. Both of these potential endogeneity problems in the site selection process make it difficult to assess whether a branch campus opening leads to economic growth in the local area or vice versa. Our empirical strategy aims to account for such endogeneity.

A second problem with measuring the impact of branch campuses is identifying the "local" community that likely could be affected and gathering the corresponding economic indicators for that "local" area. Texas has geographically large counties, and the true catchment area of a branch campus might represent only a fraction of the economic volume measured in the typically available administrative data on county-wide economic indicators. While county-level data are the lowest geographic unit for which annual administrative data on economic activity are historically available, they may not capture the true catchment area of a branch campus. We attempt to identify the true catchment area more precisely by focusing on the much smaller census tracts and their proximity to new campuses. However, while historical administrative data are available for each census tract, they are only available once a decade, which is not sufficiently frequent to

college or university. The precise definitions are included in the Tennessee Higher Education Commission's Academic Policy for Off-Campus Instruction A 1.4A (available at https://www.tn.gov/content/dam/tn/thec/bureau/aa/academic-programs/program-approv/aca-pol/CC_Univ_Off_Campus_Policy_Website.pdf, last retrieved December 23, 2023). In Texas, we include locations that offer "off campus face-to-face" instruction according to the Texas Higher Education Coordinating Board's Distance Education Program Inventory (available at https://apps.highered.texas.gov/program-inventory/, last retrieved December 23, 2023).

study the effect of newly established branch campuses. Additionally, even if we focused on the county-level, the smallest area covered by administrative data, GDP data would only be available after 2001, making it difficult to account for openings of branch campuses decades earlier.

To solve these problems, we developed a regionally disaggregated metric based on daytime satellite imagery and use it to study the effects of branch campus openings in this paper. This metric allows us to create historic, annual economic data at the census tract level. While recent work in economics and geography has frequently utilized nightlight satellite imagery as a means for measuring economic conditions (e.g., Bazzi et al., 2016; Ebener et al., 2005; Henderson et al., 2018; Lee, 2018; Sutton and Costanza, 2002), we apply a novel approach that uses daytime satellite imagery to proxy economic activity at a much more disaggregated level by deriving land-cover classifications (Lehnert et al., 2023). In comparison to other common satellite-based economic proxies (e.g., night light intensity), our proxy offers higher precision in predicting economic activity at smaller geographic areas. This property of the proxy allows us to study the effects of branch campus openings at the level of disaggregation at which the effects are most plausible based on typical empirical commuting patterns. Moreover, this novel approach offers an extended, annual time series back until 1984, allowing us to consider a significantly larger number of historic branch campus openings in our analyses. The level of disaggregation of daytime satellite imagery allows us for the first time to isolate the economic activity in close proximity to branch campuses (treated areas) in comparison to other (non-treated) areas for the period of heavy expansion of branch campuses.

We use multiple empirical strategies to identify the effect of college branch campuses on local economic growth. First, we exploit the longitudinal structure of our data by estimating fixed effects (FE) models to determine how the establishment of a branch campus impacts the local economy. We apply a traditional difference-in-differences (DD) approach that captures time-invariant unobservable characteristics of census tracts for both Tennessee and Texas, respectively. Second, we extend our DD model to account for potential treatment effect heterogeneity (Callaway and Sant'Anna, 2021; Sant'Anna and

Zhao, 2020). This approach more fully considers both the dynamic nature of the impacts as well as the staggered treatment timing. Both the traditional and the heterogeneity-robust DD results suggest a positive association between branch campuses and economic growth. According to our most conservative estimate from the heterogeneity-robust DD model, a branch campus opening is associated with a GDP growth of 1.2 percent in Tennessee and 5.0 percent in Texas.

While the DD approaches allow us to understand some differences in outcomes across different locations, the assumptions necessary to establish causality in such models may be difficult to justify. To better establish causality, we additionally use an instrumental variable (IV) approach. We were able to construct for Texas an instrument that solves the problem of endogenous branch campus location decisions. Our instrument exploits regional differences in the incentives to create new branch campuses based on differences in taxing rights across campuses. The IV results, which we regard as a more credibly causal estimate, similarly reveal positive and significant impacts of branch campus openings, amounting to a local effect on GDP growth of 13.4 percent according to our most conservative estimate. We also provide suggestive evidence on potential mechanisms. We find that the increase in the number of degrees produced corresponds to the type of campus created; moreover, we find that employment in health and education, the most common programs offered at branch campuses, increases after the establishment of a branch campus. These improvements suggest that human capital development drives the creation of business opportunities and jobs.

The paper proceeds as follows. Section 2 outlines the relevant institutional background on college branch campus openings. Section 3 describes our data and Section 4 our methods. Section 5 presents our main results, including both the DD and IV specifications. Section 6 offers various robustness checks that support our main results. Section 7 discusses the results and concludes.

2. Institutional Background and Setting

We focus on Texas and Tennessee because their expansion of branch campuses was similar to national trends. They both substantially expanded branch campuses in the early 2000s, thus helping accommodate an increase in college enrollment. Programs commonly offered at branch campuses include health professions, education programs or computer science, as well as business management and public administration or social services.[7] By offering such programs, branch campuses provide an affordable entry point into higher education, particularly for the economically disadvantaged students in a region who are more likely to attend college if a campus is closer to their home. They also increase the pool of trained skilled workers in a region and thereby create an environment that is conducive to subsequent economic expansion, often in more knowledge-intensive jobs, and encourages the emergence of new firms. For example, with computer science degrees the new graduates may work as computer support specialists or IT technicians or, if they move on to four-year colleges, they may work in software engineering. With degrees in health professions, graduates may directly enter the labor market by working as nursing assistants, or move on to a four-year program and work as a registered nurse, a healthcare administrator, or a therapist. With education degrees they may directly enter the public or private labor market by working as teaching assistants, classroom aides, or early childhood educators, or move on to a four-year program to earn a bachelor's degree and become schoolteachers (after an additional certification), educational administrators, or curriculum developers.

By producing graduates with either two- or four-year degrees, branch campuses help strengthen the human capital assets of a local economy. As such, the establishment of a new branch campus can foster local economic growth. Indeed, the rhetoric used when Texas policymakers announced branch campuses focused on expanding training and stimulating regional economic development. For instance, when Texas A&M established a branch campus in Fort Worth, policymakers made claims around establishing "an

[7]Information on programs in this section only represents Texas and was gathered from the Texas Higher Education Coordination Board's program inventory at https://apps.highered.texas.gov/program-inventory/ (last retrieved December 23, 2023).

additional talent pipeline," closing "gaps in city and state's workforce" in various careers and creating "growth and opportunity" to the area (Olivares, 2022). When the University of North Texas opened a branch campus in Frisco, Frisco Mayor Jeff Cheney made similar claims (Juarez Monsivais, 2018): "Affordable, quality education is an integral part of being a vibrant, innovative and sustainable community ... It also boosts economic development, which benefits Frisco and our entire region." Our research can establish whether such claims are justified.

3. Data

We construct two novel datasets to be able to study economic effects of campus openings at a very local regional level. The first dataset focuses on branch campus openings (our main independent variable). As information on opening dates and specific geographic locations is not readily available in single administrative databases, we assembled these data for Tennessee and Texas.[8] In Tennessee, we were able to obtain administrative data on branch campus openings via two separate data requests filled by the Tennessee Higher Education Commission and Tennessee's community and technical college system (TBR – The College System of Tennessee). In Texas, we were able to obtain a list of currently operating branch campuses from the Texas Higher Education Coordinating Board and conducted an extensive web search and phone survey to collect the opening dates of each campus.[9] We define a branch campus' opening date as the date that a campus began offering classes and enrolling students.[10]

Our second dataset focuses on regional economic activity as our outcome variable. Data on economic activity are not available at small enough local levels and particularly not for historical time series. As such, we apply Lehnert et al.'s (2023) novel methodology to construct a proxy based on daytime satellite imagery that measures local economic

[8]Appendix Figures A1 and A2 show maps of the campus locations in Tennessee and Texas, respectively.

[9]We leveraged institution websites as well as local news articles to find branch campus opening dates.

[10]While the major part of the data assembly took place in 2021 with then-available methods, in fall 2023 we were able to use ChatGPT-4 through Bing Chat for an additional search and extended our database. Our findings are robust to including or excluding the information retrieved from Bing Chat.

activity. Details are described in the following section. Given that counties are smaller in Tennessee than in Texas, our choice of states also provides some contrast in the saliency of our more localized measure of economic activity as compared to county-level economic variables.

3.1. Construction of Proxy for Local Economic Activity

We construct a proxy for local economic activity that allows us to create annual economic data for regional levels as small as U.S. census tracts. This methodology uses a machine-learning algorithm to classify pixels in the satellite data into six different land-cover categories—built-up areas, grass, forest, cropland, areas without vegetation or buildings, and water—based on the spectral reflectance in different wavelengths. The variation in this regional land-cover composition explains a significant part of the variation in regional economic activity.

Lehnert et al.'s (2023) proxy offers two major advantages over other extant metrics. First, the authors show that it has a high validity for very small regional units (e.g., units as small as one square kilometer). Therefore, we can disaggregate our outcome to regional units smaller than those available in administrative statistics (which have counties as the smallest regional units). At such disaggregated levels, the proxy also achieves higher precision in predicting economic activity at disaggregated levels than other common proxies such as night light intensity. This high validity at disaggregated levels allows us to identify local developments around newly opened branch campuses, which we expect to occur within a limited radius of a few dozen miles around it. Thus such developments may be unobservable at the county level, the most disaggregated metric available in public data. Second, the proxy offers a consecutive and consistent annual time series starting in 1984, extending administrative statistics (which start in 2001) and night light intensity data (which start in 1992).[11] This extended time series allows us to

[11] We follow the suggestion in Lehnert et al. (2023) not to use observations where more than 10 percent of a region's area is covered by clouds (i.e., each time that the satellite passed over that particular region, making it impossible to observe ground cover in those years) and observations where the number of built-up pixels deviate too strongly from the median number of built-up pixels among all observations of a region. In Texas, we additionally exclude nine census tracts at the border to Mexico from our

investigate the regional economic activities around all branch campuses that opened after 1984. With many branch campuses having opened in the 1980s, this increased variation greatly expands our sample and facilitates our estimations.

To construct the proxy for regional economic activity at the census tract level, we proceed in two steps. As a first step, we train an OLS model on the land-cover classification based on daytime satellite imagery for the entire continental U.S. to obtain highly reliable estimation coefficients for predicting economic activity at the census tract level. In doing so, we use county-level GDP data which are available from the Bureau of Economic Analysis for the years 2001 through 2020.[12] In addition, we calculate each county's area belonging to one of the six land-cover categories measured as the number of satellite data pixels per category. We take the natural logarithms of both the GDP and land-cover measures. Since we intend to use the county-level coefficients from the predicted model to predict census-tract level GDP, we standardize all variables before the estimation.[13] We then estimate Equation 1 as follows:[14]

$$Y_{jt} = \lambda + \kappa LC_{jt} + \nu_{s[j]} + \tau_t + \mu_{jt} \tag{1}$$

where Y is standardized log GDP for county j in year t, LC is a vector including the six standardized log pixel counts per land-cover category for county j in year t, ν_s is a set of state dummies, τ_t is a set of year dummies, and μ is the error term.[15] The standardization is necessary to use the obtained coefficients for predicting GDP at a different regional level, in our case the census tracts. The OLS model explains as much as 58.8 percent

analyses, because a visual inspection of the land-cover classification revealed a time-constant pattern of misclassification. From 1984 through 2020, we thus do not use the land-cover classification for 2.9 percent of the potential census-tract observations in Tennessee and 3.2 percent of the potential census-tract observations in Texas. Again following Lehnert et al. (2023), we can impute most of these observations as we use the three-year moving average of the GDP prediction as dependent variable in our analyses. After this imputation, we can use 99.5 percent of the potential census-tract observations in Tennessee and 98.8 percent of the potential census-tract observations in Texas.

[12]Available at https://apps.bea.gov/regional/downloadzip.cfm (last retrieved June 20, 2022).

[13]We standardize using the mean and standard deviation of county GDP across the entire Bureau of Economic Analysis sample of counties.

[14]Appendix Table A1 shows the results of this estimation.

[15]In addition to this set of explanatory variables, we follow Lehnert et al.'s (2023) suggestion and include a measure for cloud cover in the satellite data, which affects only very few observations, to further improve the prediction.

(adjusted R^2) of the county-level variation in GDP across the entire U.S.[16] Additional validation analyses across states further reveal that the proxy's validity is even higher for small regional levels (e.g., 90.6% of the variation in GDP in Tennessee, a state with small average county size), thus emphasizing its validity as a proxy for census tract-level economic activity.

As a second step, we use the OLS estimation coefficients of the variables in LC to obtain a census tract-level prediction of standardized log GDP. Ideally, we would estimate the same model as in Equation 1 except that we would like to estimate it at the census tract level. However, as we cannot observe GDP at the census tract level, we assume that the land-cover metrics have the same relationship at the census tract level as at the county level, and given our standardization in Equation 1, we can use the number of pixels per land-cover category to then predict census tract-level GDP. This procedure thus provides us with a prediction of standardized log GDP as an annual measure for census tract-level economic activity starting in 1984. We use these data to estimate the effect of opening a branch campus on the regional economic activity in a rather precise catchment area around the new campus.

3.2. Definition of Catchment Areas

To define the radius of impact and thus the catchment area of a new campus, we make a consideration based on commuting distance. In 2020, the last year within our study period, the mean one-way commuting time was 25.4 minutes in Tennessee and 26.6 minutes in Texas.[17] Therefore, we decide to use a 25-mile radius to correspond with these commuting times.[18] However, in Section 6.1.1 we also perform robustness checks using a 10-mile radius as a very localized lower bound and a 40-mile radius as a geographically

[16] The percentage of the explained variation in county-level GDP is thus in line with Lehnert et al.'s (2023) original analysis, which finds that the proxy explains 62.3 percent of this variation in Germany.

[17] According to data from the American Community Survey available at https://data.census.gov/table?q=commuting%20distance&g=040XX00US47,48&y=2020 (last retrieved January 2, 2024).

[18] At an average speed of 62.9 miles per hour on all traffic roads estimated for 2015 (see De Leonardis et al., 2018), these numbers correspond to an average commuting distance of 26.6 miles in Tennessee and 27.9 miles in Texas. Given that the average commuting time has been increasing throughout our observation period (Burd et al., 2021) and was likely much smaller at the start of our observation period, we decide to use a slightly smaller radius of 25 miles in our main specifications.

more widespread upper bound of an approximate commuting zone around the new branch campus.

Table 1 shows the distribution of treated units in Tennessee and Texas under the 25-mile treatment radius definition during our estimation period (1984–2020). In Tennessee, we observe 69 branch campus openings, resulting in 1,481 of 1,701 (87.1%) census tracts treated in any year of the sample and 25,084 of 62,630 (40.0%) of the observations in our regression sample representing treated observations. In Texas, these numbers amount to 65 branch campus openings, 4,536 of 6,875 (66.0%) census tracts treated in any year of the sample, and 64,940 of 251,680 (25.8%) treated observations. Tables A2 and A3 in the Appendix show this distribution for the alternative 10- and 40-mile radii.

4. Methods

We apply three different econometric methods to estimate the impact of branch campus openings on local economies. First, as a baseline model we use a DD empirical strategy to estimate the effects, applying the treatment radius of 25 miles:

$$\widehat{Y_{it}} = \alpha + \beta BranchCampusOpen_{it-4} + \gamma_i + \delta_t + \epsilon_{it} \tag{2}$$

$\widehat{Y_{it}}$ is our proxy for GDP in tract i in year t obtained through the procedure described in Section 3.1. $BranchCampusOpen_{it-4}$ is a binary indicator equal to 1 for the tracts within the specified radius in the year a branch campus opens and each subsequent year (i.e., the indicator remains equal to 1 in all years after the campus opens). We lag this variable by four years to account for the time until the first cohort of students graduates from a newly opened campus and subsequently potentially contributes to local economic activity if they work near that campus. With an average duration of almost 3.5 years for completing an associate degree (Shapiro et al., 2016) and a minimum time of four years for completing a bachelor's degree, a lag of four years is the most conservative lag we can choose. γ_i represents tract-level FE, and δ_t represents year-level FE. By including tract-level FE, we ensure that our identification relies on new branch campus openings

Table 1: Branch Campus Openings, Treated Census Tracts, and Treated Observations in Tennessee and Texas, 1984–2020

	Tennessee		Texas	
	N	%	*N*	%
	(1)	(2)	(3)	(4)
Branch campus openings (after 1984)	69		65	
Census tracts	1,701	100.0	6,875	100.0
Treated census tracts	1,481	87.1	4,536	66.0
Census tract year-observations	62,630	100.0	251,680	100.0
Treated census tract-year observations	25,084	40.1	64,940	25.8

Notes: Table presents descriptive statistics for a treatment radius of 25 miles.

throughout the period we analyze. We estimate our model with standard errors clustered at the census tract level (ϵ_{it}).

Second, we apply Callaway and Sant'Anna's (2021) heterogeneity-robust DD estimator (henceforth CS-DD). While the above DD model deals with time-invariant regional characteristics that potentially influence branch campus location decisions, it does not consider (a) that the impact of a branch campus might not be inherently constant over time and (b) that differences and treatment timing might bias the results by attaching different weights to each campus opening (for a survey of the corresponding literature, see de Chaisemartin and D'Haultfœuille, 2023); the CS-DD estimator addresses both these issues.

Third, as neither conventional DD nor CS-DD may fully solve endogeneity problems, we also estimate the impact of branch campuses using an instrumental variables strategy. However, this is only possible for Texas due to its unique institutional setting. We develop a new instrument based on the existence or non-existence of institutionalized incentives to create additional branch campuses that are exogenous to the colleges. Although branch campuses may often target campus locations based on economic characteristics of the nearby community, there is an important exception that provides the basis for an alternative identification strategy in Texas.

To understand this exception, we review the two ways in which Texas allows for the creation of community colleges. The first way relies on the state. The Texas Higher Education Coordinating Board can unilaterally create a community college. Community colleges created in this way rely on state appropriations for financing and have no local taxing authority. The second way to create a community college relies on a set of school districts joining forces. Multiple districts can join to form a community college district. The school districts have taxing authority, and they can grant some of that taxing authority to the community college district that they formed. These community college districts (and their boundaries) were largely formed over 50 years ago. About 30 percent of counties in Texas have a community college district with taxing authority, and the location of these districts is shown in Figure 2, where the shaded areas denote taxing districts.[19]

Community colleges with taxing authority charge in-district and out-of-district (higher) tuition rates. Out-of-district tuition rates are on average 56 percent higher than in-district rates,[20] and these community colleges have incentives to establish branch campuses near the borders of their taxing district to "capture" out-of-district enrollments that strengthen their revenue or to "protect" potential enrollment loss to other community college districts. We assume that the additional out-of-district tuition price exceeds the marginal cost of educating a student, so that the district has a stronger incentive to establish a branch campus.

Over the time period that we study in our paper, changes in the taxing authority of any community college districts did not occur; however, as new branch campuses are created both inside and outside of community college districts, the incentives for subsequent creation of branch campuses are subject to change. As such, we create instruments based on the interaction between a taxing district (time invariant) and the proximity of the census tract to existing branch campuses (time variant). More specifically, our set of instrumental variables comprises the log distance from a census tract (centroid) to the closest branch campus outside of its natural commuting zone (lagged by nine years)[21] and the interaction of this log distance with a dummy for whether the county in which a tract is located has a community college district with taxing authority.

To understand the instrument, consider Figure 3 as an example that visually explains the logic of our IV. Suppose that leaders are considering whether or not to establish a campus in the hypothetical location marked by the blue cross in panel A. This location is situated in a non-taxing district, with its catchment area of a 25-mile radius indicated by the light-blue shade in a stylized manner. If they were to establish a campus and assume this likely catchment area, its viability as a site would depend on whether it can attract

[19]As geographic data delineating the exact taxing district borders are not available anywhere, we manually reproduce the taxing district borders in ArcGIS using a PDF map provided by the Texas Association of Community Colleges as a basis (available at https://tacc.org/sites/default/files/documents/2018-10/17r0057_taxing_districts.pdf, last retrieved December 10, 2022).

[20]See http://www.collegeforalltexans.com/apps/collegecosts.cfm?Type=1&Level=2 (last retrieved May 7, 2024).

[21]The nine-year lag in the instrument corresponds to a five-year lag respective to the campus opening, because we lag the campus opening by another four years as explained in Equation 2.

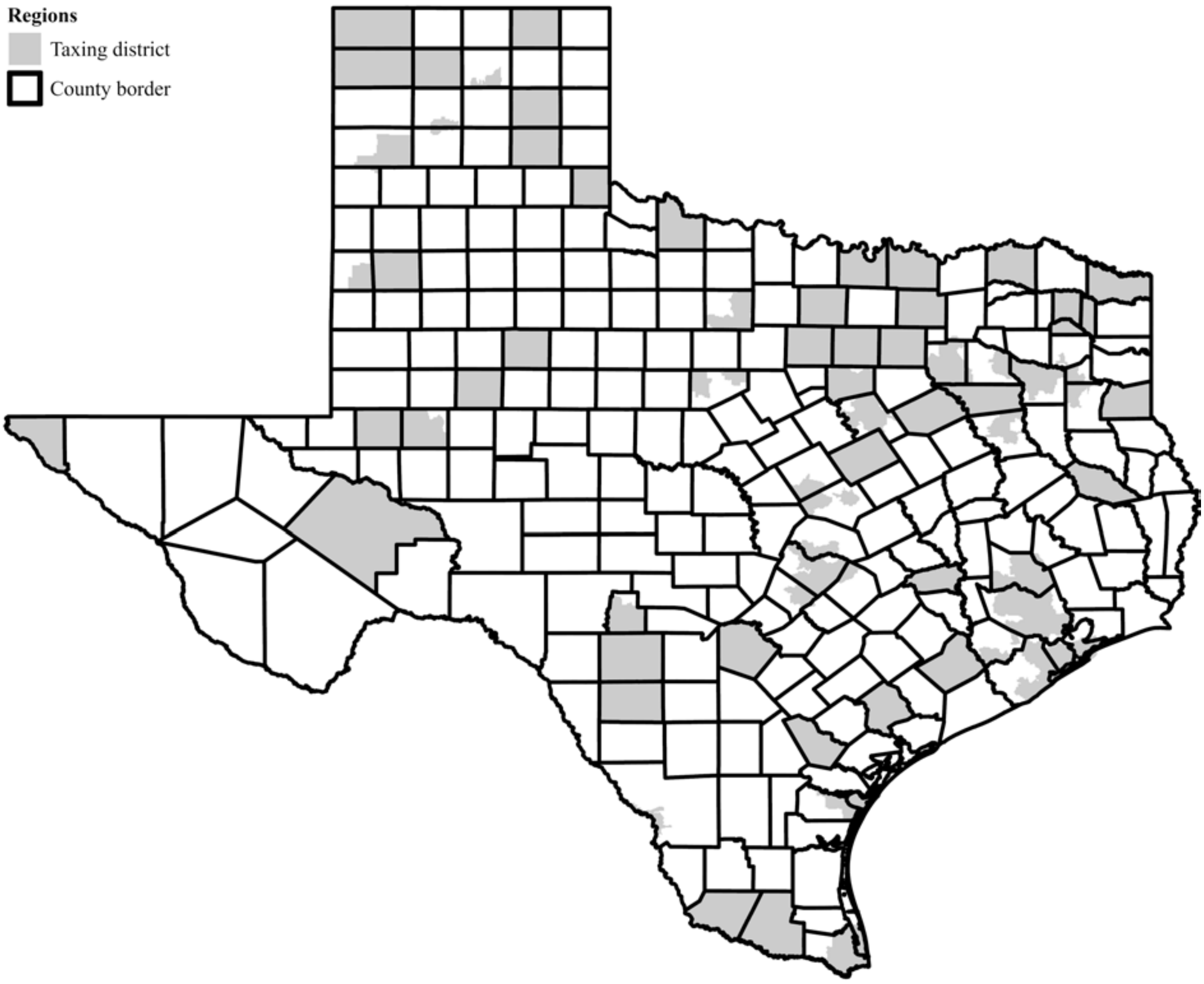


Figure 2: Texas Community College Taxing Districts

market share based on nearby competitors. As the distance to existing branch campuses located inside the catchment area of the hypothetical branch campus location (indicated by the dotted arrow) affects the treatment status of the census tract in which the campus would be located, we do not consider the distance to these campuses in constructing our instrument. Instead, we measure the distance to the nearest campus outside of its catchment area (indicated by the solid arrow) to proxy for such considerations on competition. However, this distance by itself is not enough. It may not fully satisfy the exclusion restriction if the distance is related to economic growth. We need an exogenous source of variation.

This is where the taxing districts have importance. In a taxing district, there is an incentive to establish the campus closer to its border. For the hypothetical branch campus location in panel B, which is situated within a taxing district, competitors matter but the financial incentives (56% higher tuition) for students outside the district make it so that the distance to the nearest competitor loses importance as there are incentives to create campuses within the taxing district anyway. Put differently, the distance to potential competitors plays a smaller role for the hypothetical branch campus location in panel B than for that in panel A because of the additional financial incentive due to higher tuition fees. Therefore, the establishment of a branch campus is more likely in the location indicated in panel B than in the location indicated in panel A. Empirically, to model this mechanism we interact our distance measure with a dummy variable indicating whether the census tract is located inside a taxing district or not.

Our first-stage estimates (appendix table A4, column 1) confirm this mechanism and are thus in line with our expectations. Being in a taxing district changes the relationship with distance making it so that the added incentives to establish a branch campus reverse the distance relationship. Put differently, the closer the distance to competitors, the less likely that a branch campus forms nearby; however, for taxing districts, the role of the distance to competitors is offset due to the taxing authority and hence has a smaller influence on campus location decisions. Thus, our instrument captures incentives for branch campus creation that result from both the regional necessity of college provision

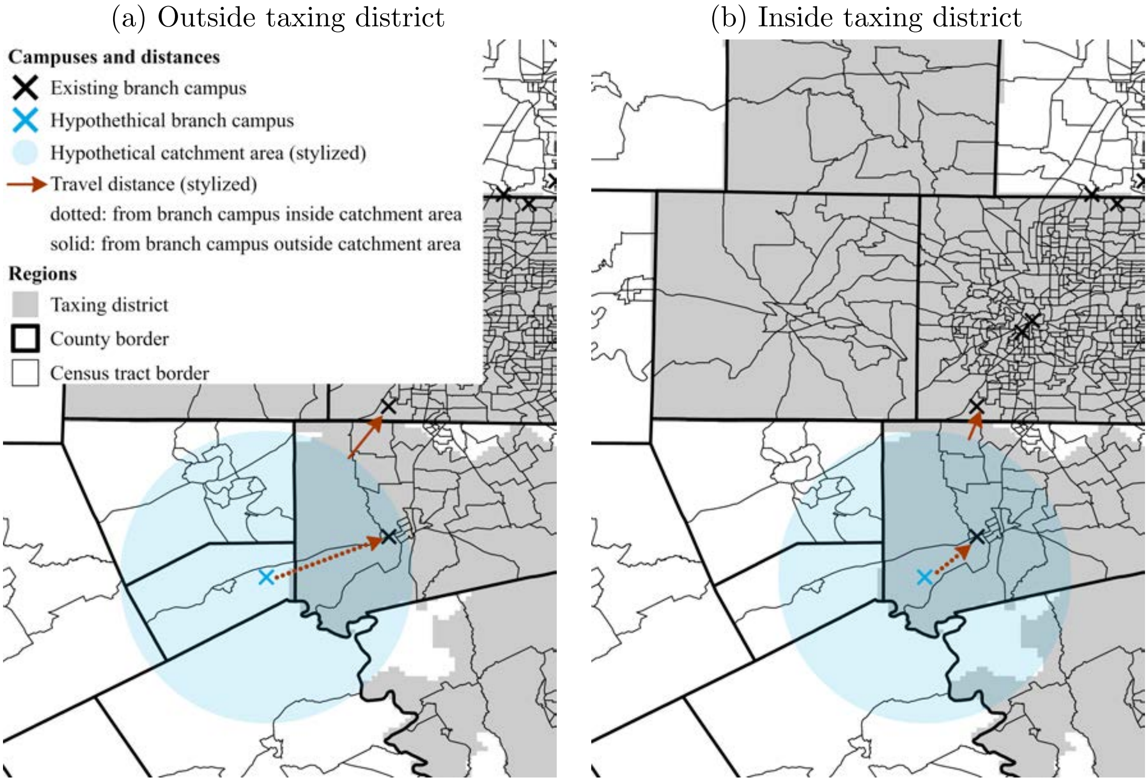


Figure 3: Hypothetical College Branch Campus Locations as Example for IV Logic

Notes: The maps show an area in the southeast of Dallas, with the blue crosses indicating hypothetical branch campus locations, one outside a taxing district (panel A) and one inside a taxing district (panel B). The areas shaded light blue highlight census tracts within the catchment area of the hypothetical branch campus locations. The dotted arrows indicate the distance to existing branch campuses inside the hypothetical catchment area, which we do not consider in constructing our instrument. The solid arrows indicate the distance from the border of the hypothetical catchment area to the closest existing branch campus outside it, which we use in in constructing our instrument.

(if other branch campuses are located only far away) and the possibility to generate taxing revenue (if a college has taxing authority in a region). The identifying assumption underlying this IV approach is that these incentives influence the location decisions for branch campuses independent of economic development.

5. Results

Table 2 presents our estimates of the effect of branch campus openings on economic activity in Tennessee (columns 1 and 2) and Texas (columns 3 through 5) with our 25-mile radius of impact. Columns 1 and 3 present the traditional DD estimates, columns 2 and 4 the CS-DD estimates,[22] and column 5 the IV estimates, which are available only for Texas. The indicator for the branch campus equals one in the year of a branch campus opening within the catchment area and in all subsequent years, with a four-year time lag.

We see consistently positive and statistically significant estimates, suggesting that local economies with a branch campus opening see larger increases in GDP than local economies without a branch campus opening. The smaller magnitude of the estimates for Tennessee compared to Texas may come from the fact that Tennessee's expansion of branch campuses outpaced the growth in enrollment (as Figure 1 indicates), and that by the end of our observation period relatively few census tracts in Tennessee remain untreated (as Table 1 indicates). Tennessee created branch campuses that continued to lower average enrollment across all campuses. By contrast, enrollment in Texas kept pace with the expansion of branch campuses. The generally larger coefficients in Texas may indicate that the branch campus openings are just responsive to population growth in Texas but not providing disproportional supply of new branch campuses. Population growth appears to spur the state or institution to open a branch campus, and increasing access to higher education enhances economic growth in locations with population growth.

The coefficients obtained through CS-DD estimation (columns 2 and 4) are only roughly

[22]We use the `csdid` package in Stata to implement this estimator (described in Callaway and Sant'Anna, 2021 and Sant'Anna and Zhao, 2020) following Roth et al.'s (2023) guidance for DD designs with staggered treatment timing.

Table 2: Estimates of Branch Campus Effect on Economic Activity in Tennessee and Texas, 1984–2020

	Tennessee		Texas		
	DD	CS-DD	DD	CS-DD	IV
	(1)	(2)	(3)	(4)	(5)
Branch campus	0.039***	0.035***	0.160***	0.141***	0.361***
	(0.008)	(0.011)	(0.007)	(0.007)	(0.119)
Observations	62,630	62,581	251,680	251,641	251,680
Number of census tracts	1,701	1,701	6,875	6,875	6,875
Within-R^2	0.207	n/a	0.191	n/a	0.166

Notes: The dependent variable is the predicted standardized natural logarithm of GDP. In the DD and IV models, the treatment variable is lagged for four years so that we estimate the economic impact of a branch campus four years after its opening date. The treatment radius is 25 miles. All models include constant, census tract FE, and year FE. The CS-DD models use fewer observations because they consider only observations with pair balance. Standard errors clustered at the census tract level in parentheses.

ten percent smaller in magnitude compared to the coefficients obtained through traditional DD (columns 1 and 3) in both Tennessee and Texas, suggesting that not accounting for differences in treatment timing leads to only a very moderate overestimation of the branch campus effect. In comparison, the coefficient obtained through IV estimation in Texas (column 5) is more than twice as large as the coefficient obtained through CS-DD estimation (column 4). We interpret this larger magnitude of the coefficient as resembling a local average treatment effect, that is, the effect of opening a branch campus in regions that comply to the incentive structure to open a branch campus provided by our instrument. The compliers are likely to be in the catchment area of college campuses in regions that are relatively underdeveloped. As such, the relative growth compared to the baseline could indeed be that much larger.

Transforming the coefficients into interpretable metrics requires some reverse engineering. We are predicting standardized growth across regions, and the impacts are in standard deviation units within the respective census tract over time. So, for example, the estimated effect of 0.160 in column 3 for Texas corresponds to an increase in economic activity of 0.160 standard deviations of predicted log GDP on average once a campus opens. For Tennessee, this effect amounts to 0.039 standard deviations. To translate this effect into a more interpretable metric, i.e., GDP growth, we can do back-of-the-envelope calculations based on a few reasonable assumptions. When we outlined our prediction models for economic growth, we standardized the dependent and independent variables across the U.S. distribution. To move our estimates in Table 2 to be GDP numbers, we have to find a way to decompose the county-level GDP into the census-tract GDP. To do this, we try two assumptions. One is that economic activity is uniformly distributed across all census tracts. While this distribution is likely infeasible, it provides a lower bound for the estimates. Second, we make the more feasible assumption that economic activity is distributed according to built-up area. This provides a second, likely more realistic bound for the estimates. In each case, we can then mathematically reverse our standardization.

Under these assumptions, we produce a lower bound and a more realistic estimate of the growth in GDP associated with a branch campus opening. For Texas, the traditional DD coefficient in column 3 translates into a cumulative increase relative to the baseline of 5.8 percent in GDP under the lower-bound assumption during our observation period (1984–2020) and a 14.1 percent increase under the more realistic assumption. For Tennessee, the traditional DD coefficient in column 1 represents a lower-bound increase in GDP of 1.4 percent and a more realistic increase of 3.3 percent. For the CS-DD results, these estimated coefficients correspond to a conservatively (realistically) estimated effect of 5.0 (12.4) percent in Texas and of 1.2 (2.9) percent in Tennessee. The IV estimate in Texas corresponds to a conservatively (realistically) estimated effect of 13.4 (34.9) percent. While the effects are larger in Texas than in Tennessee, they are economically significant, even when following the more conservative approach. In relation to the mean annual GDP growth of 4.9 percent in the U.S. in our observation period (1984–2020),[23] branch campuses make a sizeable contribution to economic growth in addition to the general trend.

6. Robustness Checks

We provide a number of robustness checks to further validate the baseline model. These include estimating the baseline model using alternative specifications on the treatment radius and examining other potential exclusion zones. Moreover, we analyze potential effect heterogeneities for two- and four-year branch campus openings and discuss the time trends of the treatment effect in an event study. Finally, to provide evidence on the potential mechanisms of the branch campus effect on GDP growth, we estimate the branch campus impact on education and employment levels. Unfortunately, this education and employment information is available only for a contracted sample for few very recent time periods. Nevertheless, our estimations provide suggestive evidence.

[23]As indicated in World Bank national accounts data and OECD National Accounts data files available at https://data.worldbank.org/indicator/NY.GDP.MKTP.CD (last retrieved December 13, 2023).

6.1. Alternative Specifications

6.1.1. Changes in Treatment Radius

We start with alternative specifications on the treatment radius. In our baseline specification, we focused on a 25-mile radius because it captures the typical commuting distance to work in the states we study (see section 3.2). To evaluate whether our results are robust to alternative specification of the branch campuses' radii of impact, we repeat our estimations with radii of 10 and 40 miles. We present the results of these estimations in Table 3.

These alternative specifications show that our results hold for the larger radius of 40 miles and mostly also for the smaller radius of 10 miles. For both Tennessee and Texas, we find the same patterns of the effects when applying the 40-mile radius as in our preferred 25-mile specifications in Section V with the exception of the IV result for Texas. The estimated coefficient when applying the 40-mile radius in the IV specification becomes statistically insignificant. With such a large radius, the first-stage estimation likely does not capture the relevant density in the college distribution anymore as, particularly in rural areas, it builds on the distance to campuses that may be too far away to influence the decision of opening a branch campus, thus leading to the insignificant estimate of the local average treatment effect in the second stage. Considering the 10-mile radius, the direction and significance of the coefficients for Texas also align with those for the 25-mile radius across the different estimators we use but are smaller in magnitude. For Tennessee, however, the traditional DD estimate turns insignificant when applying the 10-mile radius and heterogeneity-robust DD estimate even turns negative and significant at the ten-percent level. We argue that in Tennessee, which is far more densely populated than Texas, 10 miles seems to be too small a radius because census tracts in the control group likely also experience a treatment effect when using such small radii. That is, results have a downward bias because control regions (e.g., 15 miles from a campus) profit from the branch campus opening as well and potentially even draw away economic activity from census tracts within 10 miles of the campus.

Table 3: Estimates of Branch Campus Effect on Economic Activity in Tennessee and Texas, 1984–2020, 10-Mile and 40-Mile Treatment Radii

	Tennessee		Texas		
	DD	CS-DD	DD	CS-DD	IV
	(1)	(2)	(3)	(4)	(5)
Panel A: 10-mile treatment radius					
Branch campus	0.003	–0.016*	0.029***	0.024***	0.362
	(0.011)	(0.009)	(0.010)	(0.008)	(0.253)
Observations	62,630	62,600	251,680	251,632	251,680
Number of census tracts	1,701	1,701	6,875	6,875	6,875
Within-R^2	0.204	n/a	0.175	n/a	0.137
Panel A: 40-mile treatment radius					
Branch campus	0.043***	0.074***	0.198***	0.170***	–0.072
	(0.006)	(0.020)	(0.007)	(0.008)	(0.136)
Observations	62,630	62,506	251,680	251,649	251,680
Number of census tracts	1,701	1,700	6,875	6,875	6,875
Within-R^2	0.207	n/a	0.175	n/a	0.153

Notes: The dependent variable is the predicted standardized natural logarithm of GDP. In the DD and IV models, the treatment variable is lagged for four years so that we estimate the economic impact of a branch campus four years after its opening date. The treatment radius is 10 miles in panel A and 40 miles in panel B. All models include constant, census tract FE, and year FE. The CS-DD models use fewer observations because they consider only observations with pair balance. Standard errors clustered at the census tract level in parentheses.

6.1.2. Changes in the Definition of Treatment or Control Group: Donut Estimations

Next, we consider two different exclusion zones to account for two potential shortcomings of our estimation strategy. First, we produce an "outer donut" estimate of our results, that is, we exclude all census tracts located between 25 and 40 miles to a newly opened branch campus. This specification changes the control group and accounts for a potential zero-sum game in economic development. Suppose, for example, that a business would have settled in the 25–40 mile radius around the campus but now moves within 25 miles of the nearest campus. In our estimation strategy, the census tracts in the 25-40 mile radius lose economic activity (causing our control groups not to stay constant) and our treatment areas within 25 miles of a branch campus increase economic activity but only at the cost of the reduced control group effect. These zero-sum games might cause us to overstate the impact of the branch campus opening. Therefore, we use a donut estimation model and exclude census tracts in the 25–40 mile radius from our estimations, thus taking only regions with a distance of at least 40 miles to a newly opened campus as control group. Panel A of Table 4 shows the results of this outer donut estimation, which reveals estimated treatment effects very similar to those obtained from our main specification in Table 2. These robust results thus rule out the zero-sum effect as an alternative explanation.

Second, we produce an "inner donut" estimate of our results, that is, we exclude the census in which the branch campuses themselves are located. This alternative exclusion zone changes the treatment group and focuses on whether the increase in economic activity results from only the campus itself. A large, sprawling campus would significantly increase new buildings in the satellite data and thus our proxy for GDP. If this is the only source of physical growth, then it may not have spurred nearby economic activity. To account for such potential problems in the treatment group, we restrict the treatment group to census tracts located 25 miles from a newly opened branch campus but that do not themselves contain the campus. Panel B of Table 4 shows the results of this inner donut estimation, which again are very similar to our main results. Therefore, the branch campus creation

Table 4: Donut Estimates of Branch Campus Effect on Economic Activity in Tennessee and Texas, 1984–2020

	Tennessee		Texas		
	DD	CS-DD	DD	CS-DD	IV
	(1)	(2)	(3)	(4)	(5)
Panel A: Outer donut estimates					
Branch campus	0.018**	0.059***	0.156***	0.138***	0.327***
	(0.008)	(0.018)	(0.008)	(0.007)	(0.093)
Observations	56,208	56,159	229,418	229,379	229,418
Number of census tracts	1,526	1,526	6,271	6,271	6,271
Within-R^2	0.202	n/a	0.204	n/a	0.186
Panel B: Inner donut estimates					
Branch campus	0.040***	0.034***	0.160***	0.141***	0.350***
	(0.008)	(0.011)	(0.007)	(0.007)	(0.117)
Observations	60,229	60,180	249,338	249,303	249,338
Number of census tracts	1,636	1,636	6,811	6,811	6,811
Within-R^2	0.206	n/a	0.192	n/a	0.169

Notes: The dependent variable is the predicted standardized natural logarithm of GDP. In the DD and IV models, the treatment variable is lagged for four years so that we estimate the economic impact of a branch campus four years after its opening date. The estimations in panel A exclude census tracts located between 25 and 40 miles from a branch campus. The estimations in panel B exclude the census tracts in which the branch campuses themselves are located. The treatment radius is 25 miles. All models include constant, census tract FE, and year FE. The CS-DD models use fewer observations because they consider only observations with pair balance. Standard errors clustered at the census tract level in parentheses.

alone is not the driver of the economic effects.

6.2. Effect Heterogeneity

6.2.1. Two-Year Vs. Four-Year Branch Campuses

To analyze potential effect heterogeneity, we first investigate two-year and four-year branch campuses separately. As these two types of campuses offer slightly different programs, they might have differential impacts on the local economy. At two-year branch campuses, the most frequently offered programs were mainly health professions, computer and information science and support programs, liberal arts types of general programs, and education programs (i.e., teaching and other school-based professions).[24] These programs provide training that enables graduates to either directly enter the local labor market or to transfer to four-year colleges. At four-year branch campuses, the most frequently offered programs were education programs, health professions, computer and information science programs, business management, and public administration and social services programs. They directly increase the highly skilled workforce in a local region and create an environment that is conducive to economic expansion in more knowledge-intensive jobs.

Tennessee and Texas differ in the percentage of branch campus openings after 1984 that belong to two-year and four-year colleges. In Tennessee, with 59 out of 69 openings, the majority belong to two-year colleges. In Texas, branch campus openings are more evenly distributed between the two types of institutions, with 26 two-year branch campus openings and 39 four-year branch campus openings. Applying the treatment radius of 25 miles, we observe in Tennessee that 1,422 out of 1,701 census tracts (83.6%) are treated by two-year branch campuses, 722 (42.4%) by four-year branch campuses, and 663 (39.0%) by both types of branch campuses. In Texas, these numbers amount to 2,610 out of 6,875 census tracts (38.0%) treated by two-year branch campuses, 3,865 (56.2%)

[24]Information on programs in this section only represents Texas and was gathered from the Texas Higher Education Coordination Board's program inventory at https://apps.highered.texas.gov/program-inventory/ (last retrieved December 23, 2023).

treated by four-year branch campuses, and 1,939 (28.2%) treated by both types of branch campuses. Appendix Table A5 includes an overview of the descriptive statistics, including the treatment variables in the regression sample.

To estimate the particular effects of two-year versus four-year campuses, we re-estimate our DD model with separate treatment indicators for each type of campus.[25] Table 5 shows the results of this estimation, repeating for comparison the pooled DD results in columns 1 and 3 and showing the separated DD results in columns 2 and 4. The findings reveal positive and significant coefficients for both types of campuses in Texas (column 4). In Tennessee, the overall estimate in column 1 appears driven by the positive and significant estimates for two-year branch campuses in column 2. However, we cannot rule out that four-year branch campuses might also have a positive effect given that we lack power with only ten four-year branch campuses openings in Tennessee during our observation period (see appendix table A5).

6.2.2. Timing of the Effects

Second, we use the CS-DD estimation results to investigate the timing of the effects. The event-study plot in Figure 4 shows the results from 10 years prior to treatment to 10 years after treatment and yields three important insights: (1) The estimates are flat and near zero in the years leading up to treatment, thus indicating parallel pre-treatment trends in both treatment and control groups. (2) They confirm the results from the conventional DD estimates, with positive and significant point estimates in Texas and in Tennessee. (3) Tennessee and Texas differ in the timing of the treatment effects. While the point estimates increase and stay significant in all post-treatment periods in Texas, the treatment effect takes about five years to appear in Tennessee. More importantly, the estimated impacts in Table 2 hide important heterogeneity where impacts tend to increase over time after the establishment of a branch campus. In sum, the findings from the heterogeneity-robust DD estimates align with our intuition that it takes a few years

[25] Note that we cannot re-estimate the CS-DD and IV models when separating between two- and four-year campuses. The CS-DD estimator does not allow modelling different types of treatment. For the IV strategy, we would require two independent instruments, one for each type of campus.

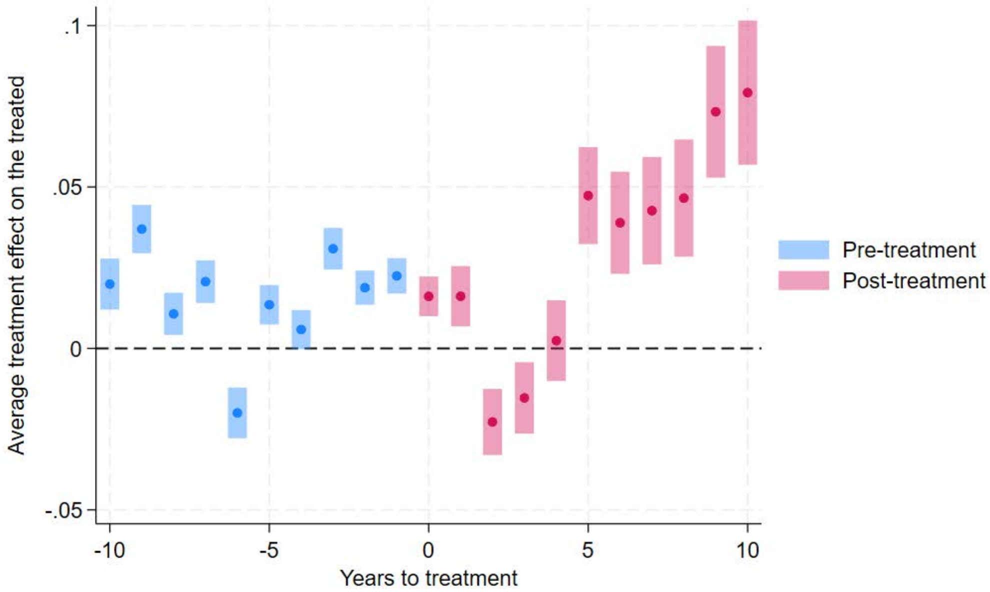
Table 5: DD Estimates of Two-Year and Four-Year Branch Campus Effect on Economic Activity in Tennessee and Texas, 1984–2020

	Tennessee		Texas	
	(1)	(2)	(3)	(4)
Any branch campus	0.039***		0.160***	
	(0.008)		(0.007)	
Two-year branch campus		0.049***		0.052***
		(0.008)		(0.010)
Four-year branch campus		–0.003		0.133***
		(0.011)		(0.008)
Observations	62,630	62,630	251,680	251,680
Number of census tracts	1,701	1,701	6,875	6,875
Within-R^2	0.207	0.208	0.191	0.188

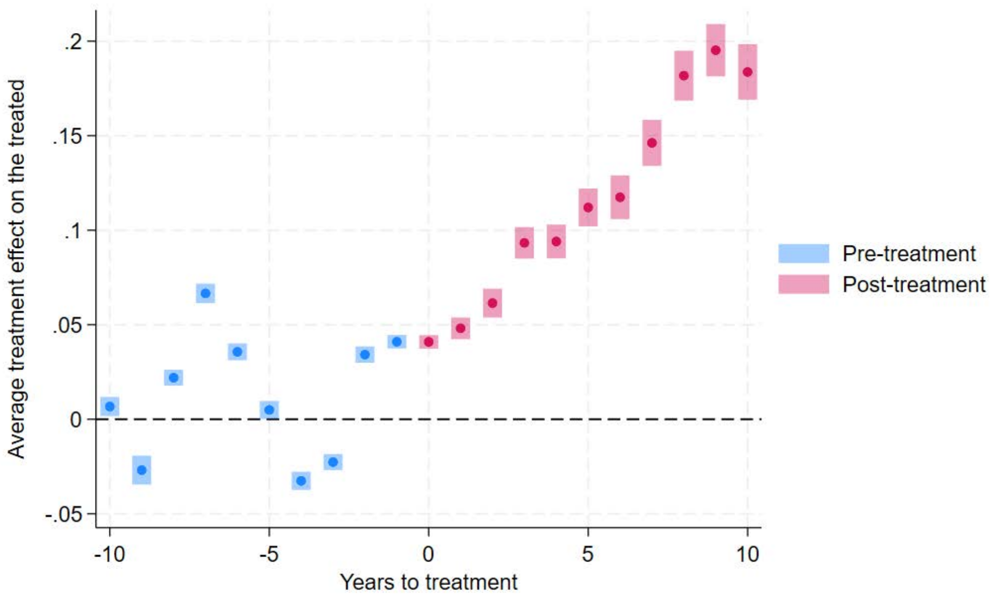
Notes: The dependent variable is the predicted standardized natural logarithm of GDP. The treatment variables are lagged for four years so that we estimate the economic impact of a branch campus four years after its opening date. The treatment radius is 25 miles. All models include constant, census tract FE, and year FE. Standard errors clustered at the census tract level in parentheses.

Figure 4: Event-Study Plot for CS-DD Estimates of Branch Campus Effect on Economic Activity in Tennessee and Texas, 1984–2020

(a) Tennessee



(b) Texas



Notes: The figure plots the point estimates and their 95% confidence intervals. The treatment radius is 25 miles.

for the impact of a branch campus to be realized.

6.3. Potential Mechanisms

Our final specification focuses on potential mechanisms that may have driven the observed differences in GDP growth. To do so, we use alternative outcome metrics which, however, are available only for the most recent years in Tennessee and Texas. This additional evidence helps us verify whether the establishment of branch campuses increased the size of the skilled labor force in the surrounding areas as one potential mechanism for increases in GDP. We use annual census tract-level data (5-year estimates) from the American Community Survey (ACS) from 2009 to 2020. While the ACS does not measure economic activity, it does provide estimates of the number of people who have attained different education levels for a subset of (i.e., the most recent) years in our main analysis. Specifically, we use three different outcome variables: the number of people with (1) some college or higher, (2) a (two-year) associate degree or higher, and (3) a (four-year) bachelor's degree or higher. As these variables equal zero for a few observations and as we want to estimate the growth in these variables associated with a branch campus opening, we use their inverse hyperbolic sine transformation as dependent variables in our regressions.

Using our same DD and CS-DD specifications from Table 2 and Equation 2, we report the estimated changes in these levels of education after the establishment of a branch campus in Table 6.[26] As panels A through C in Table 6 demonstrate, we do see the expected increase in skilled labor in this shorter ACS sample (2009–2020). According to the CS-DD estimates in columns 2 and 4, we observe an increase of roughly seven to eight percent in Tennessee in the numbers of individuals with some college or higher, the number of individuals with a two-year degree or higher, and the number of individuals

[26]We do not report the corresponding IV results for two reasons. First, given the shorter observation period of the ACS data, the IV approach could rely only on much smaller variation in the distance to other branch campuses outside census tracts' potential catchment areas, thus limiting the strength of the instrument. Second, our argument that regional taxing authority of colleges is unrelated to regional economic activity might not hold for educational attainment overall, which we measure in these estimations.

with a four-year degree or higher. In Texas, the increase in the number of people with different educational levels ranges from roughly five to seven percent. These results are suggestive only but support our assertion that these colleges are teaching colleges focused on increasing the supply of skilled workers near the new branch campuses. As branch campuses are created, we see systematic increases in the number of educated workers nearby.

Panel D of Table 6 uses the same ACS data to examine growth in specific occupations. While our satellite-based proxy does not allow us to distinguish economic growth for specific sectors, the more recent data on branch campuses suggest that two of the most prominent programs at branch campuses are in health and education fields. The ACS tracks the overall employment in these two professions combined. Therefore, we examine whether branch campus openings increase employment in these industries, again using the inverse hyperbolic sine transformation of the employment numbers as dependent variable and reporting the DD and CS-DD estimates. The DD estimates in columns 1 and 3 suggest that employment in health and education increases by roughly five percent in Tennessee and by roughly two percent in Texas after a branch campus opens. However, this finding does not hold in the CS-DD estimates (columns 2 and 4), which show a negative coefficient that is significant at the ten-percent level for Tennessee and an insignificant coefficient for Texas. The findings on employment in health and education are thus inconclusive. However, in combination with the results on educational attainment, we argue that one mechanism through which the construction of branch campuses contributes to economic growth is the provision of an improved human capital pool and thereby a potential for increased employment in the particular industries that the branch campuses emphasize.

7. Conclusion

This paper contributes to identifying the regional economic effects of educational expansions that policymakers worldwide have been using to stimulate regional growth. In the U.S., these expansions manifested as a surge in newly established branch campuses of

Table 6: Estimates of Branch Campus Effect on Educational Attainment and Employment in Education and Health in Tennessee and Texas, 2009–2020

	Tennessee		Texas	
	DD	CS-DD	DD	CS-DD
	(1)	(2)	(3)	(4)
Panel A: People with some college or higher				
Branch campus	0.045***	0.069**	0.029***	0.052***
	(0.015)	(0.034)	(0.008)	(0.013)
Within-R^2	0.140	n/a	0.143	n/a
Panel B: People with an associate degree or higher				
Branch campus	0.058***	0.080**	0.043***	0.061***
	(0.018)	(0.035)	(0.010)	(0.016)
Within-R^2	0.184	n/a	0.152	n/a
Panel C: People with a bachelor's degree or higher				
Branch campus	0.052**	0.081**	0.052***	0.071***
	(0.021)	(0.038)	(0.013)	(0.019)
Within-R^2	0.132	n/a	0.106	n/a
Panel D: Overall employment in health and education				
Branch campus	0.053***	–0.099*	0.024**	0.031
	(0.018)	(0.056)	(0.012)	(0.022)
Within-R^2	0.467	n/a	0.380	n/a
Observations	15,022	4,643	43,850	21,404
Number of census tracts	1,296	400	3,767	1,833

Notes: Dependent variables are transformed by the inverse hyperbolic sine function. In the DD models, the treatment variable is lagged for four years so that we estimate the economic impact of a branch campus four years after its opening date. The treatment radius is 25 miles. All models include constant, census tract FE, and year FE. The CS-DD models use fewer observations because they consider only observations with pair balance. Standard errors clustered at the census tract level in parentheses.

higher education institutions. We construct two novel datasets to study the relationships for Tennessee and Texas as two exemplary cases of the U.S. expansion. First, we collect historical data on the opening dates and locations of branch campuses. Second, we construct a regionally disaggregated proxy for economic activity based on a procedure that Lehnert et al. (2023) developed using daytime satellite imagery. The new satellite-based proxy offers three primary advantages: (1) it can be disaggregated at the sub-county level; (2) it is available from as early as 1984 onwards; and (3) it is available annually. All these three characteristics are necessary to investigate regional effects of new branch campuses. Combining the two datasets enables us to estimate the impact of branch campus openings on regional economic activity.

We use three different methods to estimate the effects. Overall, we find positive and statistically significant effects for both states in all estimations. First, the traditional DD approach that captures time-invariant unobservable regional characteristics shows positive effects of branch campus openings on economic activity that, in our most conservative estimate, amount to about 1.4 percent in Tennessee and about 5.8 percent in Texas. This effect is driven by two-year branch campuses in Tennessee and by both two- and four-year branch campuses in Texas. Second, the heterogeneity-robust DD estimations account for potential treatment effect heterogeneity and show that the effects increase over time. Third, the IV approach that we were able to construct for Texas exploits regional differences in taxing regulations to deal with the potential endogeneity in branch campus locations. Its results again show significant positive and even stronger effects. We also provide suggestive evidence on potential mechanisms by using educational attainment and employment statistics which, however, begin only in 2009. We find clear suggestive evidence that the increase in human capital and employment followed the same patterns as the increase in GDP after the opening of two- and four-year branch campuses. This finding indicates that regional improvements in human capital created better hiring and business opportunities, thereby also helping create new jobs for the graduates of the newly opened higher education institutions. Thus our results provide clear evidence that widely used educational expansion policies are able to meet their goals of improving regional economic outcomes by economically relevant magnitudes. The effect can be diluted, however, when the pace of branch campus construction outpaces the growth in enrollment.

Though our work contributes important novel results to the existing literature on higher education's impact on regional economies, additional work remains to be done. Our analysis includes only two states of the U.S., which is due to a lack of publicly available data on branch campus locations and opening dates. Expanding this analysis to include additional states in different regions of the U.S. or in countries around the world with different political and economic contexts can help bolster the external validity and generalizability of our results. Furthermore, additional data on (branch) campus locations (e.g., enrollment and graduate counts, information about programs and classes offered, counts of faculty, staff, or resources) would provide valuable additional insights into the role of particular campus characteristics within the larger higher education system. Unfortunately, such data are currently not available or cannot be disaggregated between branch and parent campuses, which calls for a better and harmonized statistical documentation of higher education data in the future.

Appendix

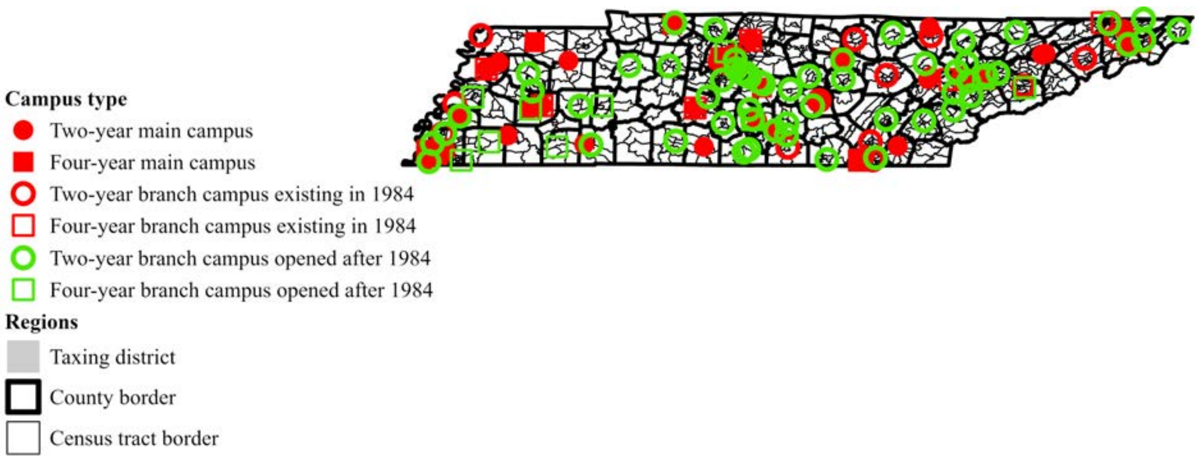


Figure A1: Campus Locations in Tennessee

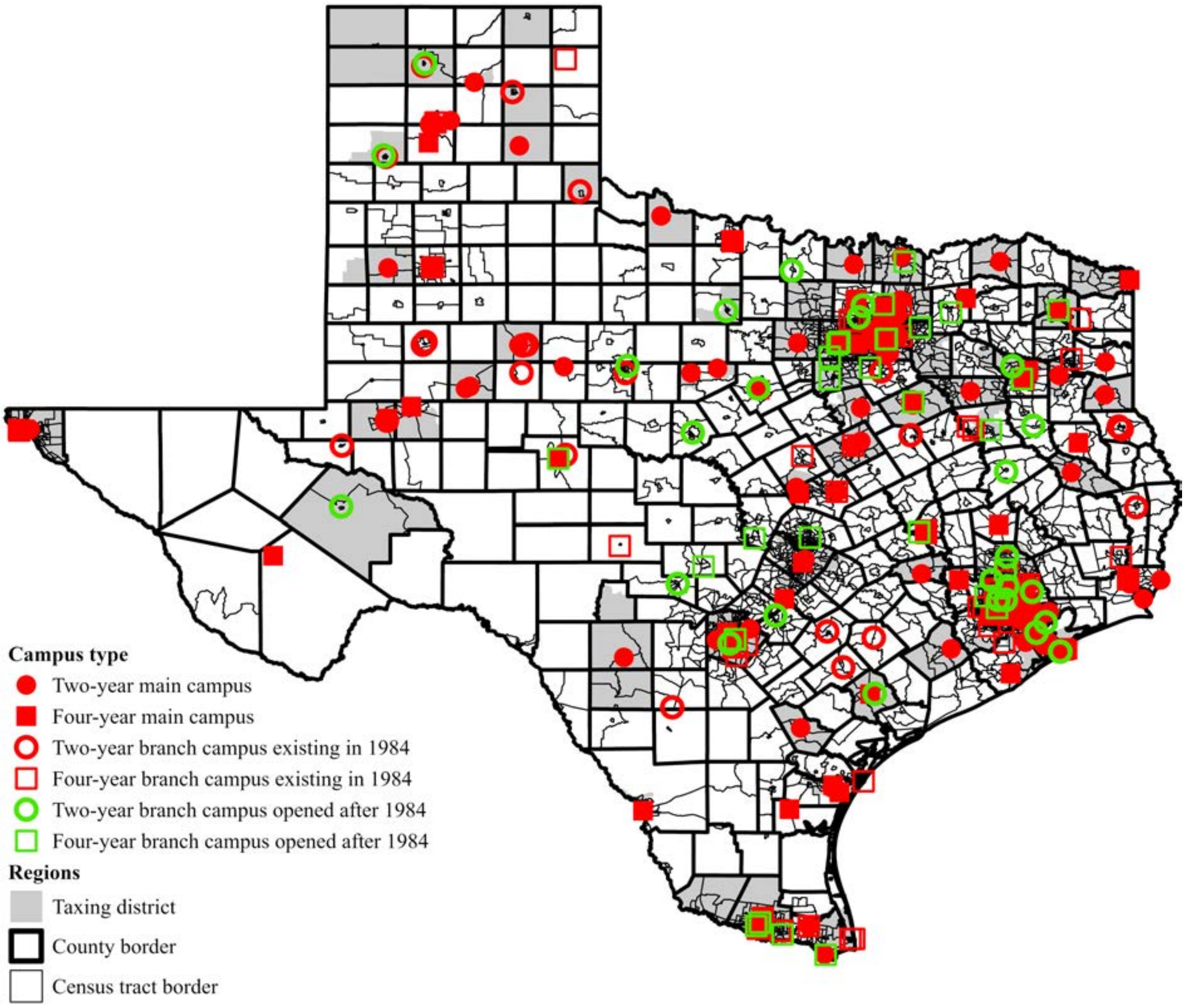


Figure A2: Campus Locations in Texas

Table A1: OLS Results for Constructing Proxy for Regional Economic Activity, County Level, 2001–2020

	(1)
ln(built-up + 1)	1.398^{***}
	(0.011)
ln(grass + 1)	-0.038^{***}
	(0.007)
ln(crops + 1)	-0.232^{***}
	(0.008)
ln(forest + 1)	-0.035^{***}
	(0.005)
ln(no vegetation + 1)	-0.828^{***}
	(0.008)
ln(water + 1)	0.115^{***}
	(0.004)
% cloud cover	0.002
	(0.002)
Observations	60,572
Adj. R^2	0.588

Notes: The dependent variable is the natural logarithm of GDP. All variables, both dependent and independent, are standardized. The model includes county and year FE. Sample comprises data from all continental U.S. states. Robust standard errors in parentheses.

Table A2: Branch Campus Openings, Treated Census Tracts, and Treated Observations in Tennessee and Texas, 1984–2020, 10-Mile Treatment Radius

	Tennessee		Texas	
	N	%	*N*	%
	(1)	(2)	(3)	(4)
Branch campus openings (after 1984)	69		65	
Census tracts	1,701	100.0	6,875	100.0
Treated census tracts	844	49.6	2,131	31.0
Census tract-year observations	62,630	100.0	251,680	100.0
Treated census tract-year observations	10,489	16.7	22,947	9.1

Note: Table presents descriptive statistics for a treatment radius of 10 miles.

Table A3: Branch Campus Openings, Treated Census Tracts, and Treated Observations in Tennessee and Texas, 1984–2020, 40-Mile Treatment Radius

	Tennessee		Texas	
	N	%	*N*	%
	(1)	(2)	(3)	(4)
Branch campus openings (after 1984)	69		65	
Census tracts	1,701	100.0	6,875	100.0
Treated census tracts	1,662	97.7	5,132	74.6
Census tract-year observations	62,630	100.0	251,680	100.0
Treated census tract-year observations	35,046	56.0	82,489	32.8

Note: Table presents descriptive statistics for a treatment radius of 40 miles.

Table A4: First-Stage IV Estimates

	Table 2, column 5 (25-mile radius)	Table 3, panel A, column 5 (10-mile radius)	Table 3, panel B, column 5 (40-mile radius)	Table 4, panel A, column 5 (Outer donut)	Table 4, panel B, column 5 (Inner donut)
	(1)	(2)	(3)	(4)	(5)
ln(Distance to closest branch campus outside catchment area)	0.075***	0.044***	0.009	0.023*	0.077***
	(0.013)	(0.007)	(0.008)	(0.014)	(0.013)
ln(Distance to closest branch campus outside catchment area) × Taxing district	–0.105***	–0.065***	–0.045***	–0.104***	–0.107***
	(0.014)	(0.008)	(0.009)	(0.014)	(0.014)
F-value of instruments	32.921***	31.143***	64.246***	159.432***	33.891***
Observations	251,680	251,680	251,680	229,418	249,338
Number of census tracts	6,875	6,875	6,875	6,271	6,811
Within-R^2	0.426	0.174	0.513	0.470	0.425

Notes: Column titles indicate the corresponding second-stage results. The dependent variable is the binary indicator for a branch campus opening and is lagged four years relative to the second-stage dependent variable. The independent variables are lagged nine years relative to the second-stage dependent variable, that is, five years relative to the first-stage dependent variable. All models include constant, census tract FE, and year FE. Standard errors clustered at the census tract level in parentheses.

Table A5: Branch Campus Openings, Treated Census Tracts, and Treatment Observations in Tennessee and Texas, 1984–2020, by Campus Type

	Tennessee		Texas	
	N	%	N	%
	(1)	(2)	(3)	(4)
Two-year branch campuses openings (after 1984)	59	85.5	26	40.0
Four-year branch campuses openings (after 1984)	10	14.5	39	60.0
Census tracts	1,701	100.0	6,875	100.0
Treated by two-year branch campus	1,422	83.6	2,610	38.0
Treated by four-year branch campus	722	42.4	3,865	56.2
Treated by both two-year and four-year branch campus	663	39.0	1,939	28.2
Census tract-year observations	62,630	100.0	251,680	100.0
Treated by two-year branch campus	24,479	39.1	29,226	11.6
Treated by four-year branch campus	5,276	8.4	52,090	20.7

Note: Table presents descriptive statistics for a treatment radius of 25 miles.

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